SISO: a conceptual framework for the construction of "stereotypical maps" in a Social Internetworking Scenario

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Abstract. In this paper we present *SISO*, a conceptual framework for the construction of "stereotypical maps" in a Social Internetworking Scenario. *SISO* aims at favoring the definition of "scientific" stereotypes in a Social Internetworking context and their use in many "scientific" applications, such as information search, trust and reputation, and so forth. For this purpose, it constructs a stereotypical map for each user. For each stereotype into consideration, this map computes how much the personal traits of the corresponding user are compliant with that stereotype. *SISO* also constructs the stereotypical map of a whole Social Internetworking Scenario; this map partitions this scenario into homogeneous regions, each formed by users connected to each other by friendship relationships and, at the same time, showing similar stereotypical traits.

Keywords: Stereotypes, Stereotypical Maps, Social Internetworking, User Similarity Detection

1 Introduction

The term "stereotype" derives from the combination of the Greek words "stereos" (i.e., solid) and "typos" (i.e., impression). It is used to indicate a popular belief about specific groups of individuals. It was initially coined in printing at the end of the XVIII Century; in its modern psychology meaning it was introduced at the beginning of the XX Century by Walter Lippmann [18]. The tendency of categorizing people into groups and of associating a "general idea", a "label" (and, ultimately, a stereotype) with each group is intrinsic in human mind. As a consequence, in human history, a lot of (both positive and negative) stereotypes have been coined; think, for instance, of stereotypes on sport, art, literature, and so forth.With the diffusion of the Web, the definition and the use of stereotypes, typical of real life, started to be also present in the Cyberspace. This phenomenon became much more marked as the Web interactivity level increased; it reached its peak with the Web 2.0 and, especially, with social networks. For instance, in Facebook, it is possible to find stereotypes such as "Lime-Lighters", "Emo's", "Philosophy Majors", "Hopeless Romantics", "Ghosts", "Stalkers", "Addicts", and so forth [2]. Analogously, in Twitter, "Fickle Followers", "Mad Scientists" and "Impulsive Twitters" can be found [1]. These kinds of stereotype could be useful in the daily communications and interactions in social networks. However, we argue that it could be possible to define more "scientific" stereotypes and to use them in many "scientific" applications.

This last idea could be even more interesting in a Social Internetworking Scenario (hereafter, SIS) which represents the current challenge of Social Networking [11]. A SIS considers more social networks simultaneously; users of these social networks can interact with each other to communicate, to share resources, to acquire opinions, and so on. An example of a "scientific" stereotype, useful in this application scenario, could be the "hub" user, i.e. a user joining more social networks who is particularly capable of favoring information sharing among them; think, for instance, of a user very trusted in a social network of cardiologists and in another one of diabetes specialists; he could favor the studies about the role of diabetes in hearth diseases. Other possible "scientific" stereotypes could be the "starters" (who are very capable of starting discussions about new topics), the "spammers", the "power users", and so on.

An investigation about stereotypes cannot leave reference contexts out of consideration. A reference context indicates a "general subject of interest" in the SIS; examples of reference contexts could be "databases", "soccer", "pop music", and so forth. As a matter of fact, a database professor could be a "starter" in the context "databases" and a "stalker" in the context "pop music", if he knows nothing about this last subject and continuously contacts many people to have information about it. A scientific investigation of stereotypes and of their applications could be performed at two different levels. Indeed, it could be possible to construct a "stereotypical map" for each user and a "stereotypical map" of the SIS in the whole. The stereotypical map of a user u_i has an entry for each context cnt_z and for each stereotype st_w into consideration; this entry is a number, in the real interval $[0, 1]$, specifying the attitude of u_i to act as st_w in cnt_z; the higher this number and the higher his attitude. For each context cnt_z, the stereotypical map of the SIS partitions this last one into regions; each region is formed by users connected to each other by friendship relationships and, at the same time, showing similar stereotypical traits. For instance, it could be possible to identify a region of "hubs", another one of "starters", a further one of "power users", and so forth. In order to investigate about our intuitions on a "scientific" use of stereotypes, in this paper we propose $SISO$ (`S`earching for the `I`nner `S`tereotypes within `O`urselves), a framework for the construction of "stereotypical maps" in a Social Internetworking Scenario.

Stereotypes can rapidly evolve over time; new stereotypes could be defined, whereas other ones could become obsolete. As a consequence, $SISO$ should be very flexible since it should allow the insertion of new modules handling new stereotypes, and the removal of existing modules handling no longer interesting stereotypes. Moreover, given a stereotype, different techniques could be defined to handle it; as a consequence, $SISO$ should allow the presence of different modules managing the same stereotype. These two facts suggest that the Component-

Based Development (hereafter, CBD) paradigm represents the best solution to be adopted for the construction of $SISO$.

From the previous description it is possible to identify three main tasks performed by $SISO$, namely: *(i)* computation of the "stereotypical degrees" of a user for the stereotypes and the reference contexts into consideration; *(ii)* construction of the stereotypical map of a user; *(iii)* construction of the stereotypical map of the SIS. Observe that these three tasks are strictly related to each other because the output of one of them is often the input for another one; as a consequence, it appears well suited to organize components into layers by following the ideas typical of the layers architectural pattern. As a consequence, $SISO$ consists of three layers, each containing one or more components. These layers are: *(i)* the *Stereotype Detection Layer*; *(ii)* the *User Stereotypical Map Construction Layer*; *(iii)* the *SIS Stereotypical Map Construction Layer*. $SISO$ represents a SIS by means of a suitable model; this last one must be capable of handling all the concepts and the relationships typical of our reference scenario. In the meantime, it must be very flexible in such a way as to allow the addition and/or the removal of components in $SISO$.

Some possible applications which could highly benefit of the stereotypical maps produced by SISO are: *(i)* enrichment of user profiles based on user behaviors; *(ii)* recommendation of users with similar characteristics; *(iii)* extraction of relationships among stereotypes; *(iv)* computation of trust and reputation of users and social networks; *(v)* team building; *(vi)* support to marketing campaigns; *(vii)* support to political campaigns; *(viii)* information search support; *(ix)* "Cold Start" problems.

This paper is organized as follows: in the next section we provide an overview of the use of stereotypes in the past literature, both in Computer Science and in other cultural fields. In Section 3 we illustrate the SIS model which $SISO$ is based on. In Section 4 we provide a technical description of $SISO$. Finally, in Section 5, we draw our conclusions.

2 Stereotypes in the past literature

As pointed out in the Introduction, the concept of stereotype, in its modern psychology meaning, was originally proposed by Walter Lippmann in his book "Public Opinion" [18]. Lippmann used this term to represent the abstract mental representation that comes in mind when thinking about a particular social group.

In sociology and psychology, the term "stereotype" is exploited to refer to the human tendency to simplify and speed up the process of perception of new persons by means of categories. Many issues have been investigated in this research area, and many works have been proposed in the scientific literature. Specifically, the use of categorical thinking in everyday life and, in particular, the cognitive dynamics of categorical social perception are discussed in [7]. The role played by stereotypical beliefs in the development of discrimination patterns is investigated in [8].

An overview of stereotypes from a cognitive perspective is proposed in [15]. In this paper, the authors focus on the motivations leading people to develop stereotypes and on the role of cognitive mechanisms in stereotype development. They define stereotypes as cognitive categories exploited by a subject when he processes information about other people. A set of experiments devoted to verify the impact of the use of stereotypes on interpersonal interactions is illustrated in [19]. A research devoted to study how reputations of lower ability (e.g., stereotypes) can act as psychological threats that undermine academic performance is presented in [10]. In this paper, the authors aim at explaining how these stereotypes can produce under-achievement and how this dynamics ultimately explains the inequalities among social groups. An interesting attempt to define a quantitative and individual measure of stereotyping can be found in [20]. This measure is based on the definition of stereotypes as probabilistic predictions that distinguish the stereotyped group from the other ones.

As for Computer Science, some attempts to investigate the concept of stereotype can be found in the literature. Indeed, stereotypes have been used in the definition of models to represent groups of users [12,26,5], in e-commerce [24,6], in the development of techniques to hasten the learning process of robots [25,22], and in several other application fields [23,9,16]. Also the strict connection between User Modeling and Stereotypes has been investigated [21]. However, the interaction of stereotypes and online social networks, and, more in general, online social communities, received a little attention in the past. In fact, to the best of our knowledge, the only attempt in this sense is the approach described in [17]. However, this paper is completely different from ours. In fact, it presents an approach that adopts social network analysis, graph theory and data mining techniques to analyze groups in a community and to cluster them in such a way as to capture stereotypes of virtual teams in the community itself.

As for stereotypes in other computer science fields, in [25] an approach to creating and exploiting stereotyped partner models to speed up the process of learning about a robot's interactive partner is investigated. In [12] the authors investigate some possible improvements in agent modeling using *reevaluative stereotyping with switching*. The possibility of exploiting stereotypes, intended as a collection of frequently occurring characteristics of users, to create models of individual users is investigated in [22]. The possible exploitation of user stereotypes to reduce the latency problem in collaborative filtering recommender systems is analyzed in [23]. The exploitation of stereotypes to compute trust and reputation in dynamic multi-agent systems is analyzed in [9]. A comparison between two alternative rule based information filtering methods, the former exploiting stereotype-based rules and the latter exploiting personal rules, is proposed in [16]. A formal evaluation method to test the accuracy and/or the homogeneity of stereotypes derived from the explicit characteristics of users is proposed in [26]. In [24] an adaptive electronic video store application, that monitors customer actions and provides dynamic movie recommendations, is proposed. In [5] the authors propose the exploitation of stereotypes for defining an intelligent inference technique to acquire information about users in an unobtrusive fashion.

An approach to deriving team stereotypes in a social community is proposed in [17].

It is worth pointing out that, to the best of our knowledge, neither an approach conceived to build and exploit user stereotypical maps in a SIS nor an approach to partitioning a SIS into regions of homogeneous stereotypes have been proposed in the past literature.

3 The underlying SIS model

In this section we illustrate the SIS model supporting $SISO$. We have to get clear from the outset that, owing to its purpose to be the underlying model of a framework following the Component-Based Development paradigm, this model must necessarily be very extensible. As a consequence, it currently represents a set of concepts and relationships very common in social networks and sufficient to support a very large number and a high variety of components; however, if, in the future, in order to implement a particular component, a further concept or a further relationship will need to be considered, they could be added to our model very easily.

As for the represented concepts, our model considers the following sets: *(i)* the set *users* of the users of the SIS; *(ii)* the set *social_networks* of the social networks of the SIS; *(iii)* the set *resources* of the resources posted in the SIS by its users; *(iv)* the set *opinions* of the opinions posted in the SIS by its users; *(v)* the set *tags* of the tags exploited by at least one user to label at least one resource or one opinion; *(vi)* the set *comments* of the comments posted by users and referring to a resource or an opinion; *(vii)* the set *evaluations* of the evaluations of the resources and the opinions performed by users; *(viii)* the set *stereotypes* of the stereotypes considered in the SIS.

In addition to these sets, which represent concepts intrinsic in a Social Internetworking Scenario, our model considers a further set which plays a key role in $SISO$, namely:

- the set *contexts* of the reference contexts of interest to the SIS. As pointed out in the Introduction, a reference context represents a cultural area, a theme; examples of contexts could be “italian literature”, “object oriented languages”, etc. Each context subsumes a set of tags strictly related to the cultural area it represents; these tags form its profile.

The relationships considered in our model often represent actions performed by users. Currently, our model considers the following relationships:

- $membership_{u_i,s_k}$; it indicates that the user u_i joined the social network s_k[1].

[1] Observe that, a user can join more social networks in a SIS; in this case, analogously to what happens in other Social Internetworking Scenarios (see, for instance, the reference scenario of Google Social Graph [3]) we assume that it is possible (in case with the support of the user himself) to know all the accounts adopted by him in the involved social networks.

- $resource\_posting_{u_i,r_j,s_k}$ (resp., $opinion\_posting_{u_i,o_j,s_k}$); it denotes that u_i posted the resource r_j (resp., the opinion o_j) in s_k.
- $resource\_tagging_{u_i,r_j,t_h,s_k}$ (resp., $opinion\_tagging_{u_i,o_j,t_h,s_k}$); it indicates that u_i specified the tag t_h as one of the tags in the label of r_j (resp., o_j) in s_k.
- $querying_{u_i,t_h,s_k}$; it denotes that u_i specified t_h in at least one of his queries in s_k.
- $resource\_accessing_{u_i,r_j,s_k}$ (resp., $opinion\_acessing_{u_i,o_j,s_k}$); it indicates that u_i accessed r_j (resp., o_j) in s_k.
- $resource\_commenting_{u_i,r_j,c_x,s_k}$ (resp., $opinion\_commenting_{u_i,o_j,c_x,s_k}$); it denotes that u_i submitted the comment c_x for r_j (resp., o_j) in s_k.
- $friendship_{u_i,u_l,s_k}$; it indicates that u_i and u_l declared their friendship in s_k.
- $resource\_evaluating_{u_i,r_j,s_k}$ (resp., $opinion\_evaluating_{u_i,o_j,s_k}$, $comment\_evaluating_{u_i,c_x,s_k}$); it denotes that u_i evaluated r_j (resp., o_j, c_x) in s_k.

Observe that opinions and resources could be considered of the same nature (for instance, an opinion could be considered as a textual resource expressing some ideas of the user posting it). Moreover, they are characterized by exactly the same relationships. In order to simplify our algorithms, in the following, wherever resources and opinions are handled in the same way, we shall use the term *information_entity* to represent both of them.

Starting from the sets and the relationships introduced above, our model defines some *derived sets* which, in their turn, represent starting sets for the algorithms implemented in the components of $SISO$. In the following we specify some of them which are very common or will be exploited in the components described in this paper. Again, the list below can be enriched with other sets if they are necessary for other components in the future. Currently, the list comprises the following sets: *(i)* pr_{u_i}; it represents the profile of the user u_i; it consists of the set of the tags mostly used by him in his past activities; *(ii)* pr_{e_j}; it represents the profile of the information entity e_j; it consists of a set of tags indicating the content of e_j (in case e_j is a resource) or the subjects of e_j (in case e_j is an opinion); *(iii)* pr_{cnt_z}; it represents the profile of a context cnt_z; as previously pointed out, this profile consists of the set of the tags subsumed by cnt_z; *(iv)* pr_{s_k}; it represents the profile of the social network s_k; this profile consists of the set of the tags mostly used therein; *(v)* $users_{s_k}$; it represents the set of the users of s_k; *(vi)* $max\_friends_{s_k}$; it represents the maximum number of friends of a user in s_k; *(vii)* $social\_networks_{u_i}$; it represents the set of the social networks joined by u_i; *(viii)* $posted\_entities_{u_i}$; it represents the set of information entities posted by u_i; *(ix)* $friends_{u_i}$; it represents the set of the users who declared their friendship with u_i in one or more social networks; *(x)* $friends_{u_i,s_k}$; it represents the set of the users who declared their friendship with u_i in s_k.

We point out that, in the following, we shall not exploit all the components of this model (for instance, the $friendship$ relationship) since, due to space constraints, we shall discuss in details only some parts of $SISO$. However, we preferred to illustrate our model in all its components.

4 Technical description of SISO

The architecture of $SISO$ consists of three layers. In its turn, each layer consists of one or more components. The three layers of $SISO$ are:

– *The Stereotype Detection Layer*; it computes the "stereotypical degrees" of a user for a set of stereotypes and a set of reference contexts. It has a component family for each kind of stereotype considered in $SISO$. As a matter of fact, given a stereotype (e.g., spammer) it could be possible to adopt different techniques to compute how much the personal traits of a user are compliant with that stereotype. Each technique could be implemented by a different component.
  Thanks to the CBD paradigm underlying $SISO$, if, in the future, a new stereotype must be analyzed, it is sufficient to add a component family to this layer.
– *The User Stereotypical Map Construction Layer*; it consists of only one component called *User Stereotypical Map Constructor* ($USMC$), which combines the results returned by the previous layer in such a way as to construct the stereotypical map of a user. As pointed out in the Introduction, this map represents a characterization of his tendency to show a behavior compliant with the ones typical of one or more stereotypes in the reference contexts into consideration.
– *The SIS Stereotypical Map Construction Layer*; it consists of only one component called *SIS Stereotypical Map Constructor* ($SSMC$), which processes the results returned by the previous layer in such a way as to construct the stereotypical map of the SIS. As pointed out in the Introduction, for each reference context into consideration, this map partitions the SIS into homogeneous regions, each formed by users connected to each other by friendship relationships and, at the same time, showing similar stereotypical traits.

Due to space reasons, in the following we describe in detail only the User Stereotypical Map Construction Layer and the SIS Stereotypical Map Construction Layer of $SISO$.

4.1 The User Stereotypical Construction Layer

This layer constructs a stereotypical map for one or more users of the SIS. It presently consists of only one component called User Stereotypical Map Constructor ($USMC$).

The User Stereotypical Map Constructor (USMC) component This component constructs the stereotypical map of one or more users. Given a user u_i, the corresponding stereotypical map $user\_st\_map_{u_i}$ consists of a matrix having a row for each context and a column for each stereotype considered in the SIS. The generic element of this matrix $user\_st\_map_{u_i,cnt_z,st_w}$ is a number, in the real interval $[0, 1]$, representing the "stereotypical degree" of u_i as far as the

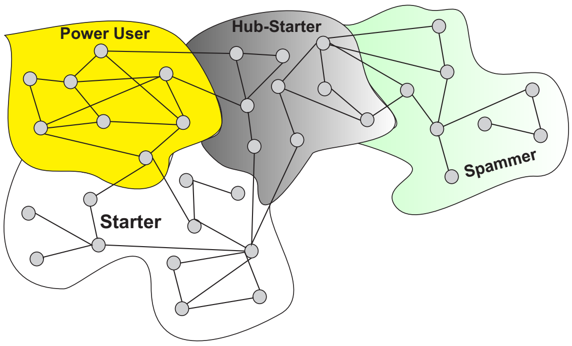

Fig. 1. A representation of the SIS Stereotypical Map associated with a certain context cnt_z

context cnt_z and the stereotype st_w are concerned. We recall that this degree indicates how much the personal traits of u_i are compliant with the features of st_w as far as the cultural area and the themes represented by cnt_z are concerned.

Given a user u_i, $USMC$ receives a vector for each component of the Stereotype Detection Layer. This vector stores the stereotypical degrees of u_i for all the contexts and for the stereotype corresponding to the component. Observe that, according to the CBD paradigm, there could be more components associated with the same stereotype; each of them implements a different approach for the computation of the corresponding stereotypical degrees. Let $st\_comp\_set_{st_w} = \{st_w^1, \cdots, st_w^y, \cdots, st_w^n\}$ be the set of all the components associated with the stereotype st_w in $SISO$, and let $std^y_{u_i,cnt_z,st_w}$ be the stereotypical degree of u_i, concerning the context cnt_z, as returned by the component st_w^y of $st\_comp\_set_{st_w}$. $USMC$ computes the generic element $user\_st\_map_{u_i,cnt_z,st_w}$ of the stereotypical map of u_i as follows:

$$user\_st\_map_{u_i,cnt_z,st_w} = agg(std^1_{u_i,cnt_z,st_w}, \cdots, std^y_{u_i,cnt_z,st_w}, \cdots, std^n_{u_i,cnt_z,st_w})$$

Here, agg is a suitable aggregation operator which returns a value in the real interval $[0, 1]$. For instance, it could represent a weighted mean of the involved parameters.

4.2 The SIS Stereotypical Map Construction Layer

This layer constructs a stereotypical map for the whole SIS. For each context into consideration, this map partitions the SIS into "regions" such that each of them consists of users having the same stereotypical traits and connected to each other by friendship relationships (see Figure 1). This layer presently consists of only one component called SIS Stereotypical Map Constructor ($SSMC$).

The SIS Stereotypical Map Constructor (SSMC) component This component constructs the stereotypical map of the SIS. Given a context cnt_z, the corresponding element $sis\_st\_map_{cnt_z}$ of the SIS stereotypical map consists of a set of graphs:

$$sis\_st\_map_{cnt_z} = \{sis\_reg^1_{cnt_z}, \ldots, sis\_reg^y_{cnt_z}, \ldots, sis\_reg^m_{cnt_z}\}$$

A graph $sis\_reg^y_{cnt_z}$ represents a region of the map and is associated with one or more reference stereotype; this association is performed by $SSMC$. The nodes of $sis\_reg^y_{cnt_z}$ denote its users whereas the edges represent their friendships.

From the previous definition we can observe that a region is characterized by the following important features: *(i)* its users are connected by friendship relationships; *(ii)* its users must have affine stereotypical traits. These features must be strongly considered in the definition of the behavior of $SSMC$; for instance, this component cannot perform only a clustering activity on the SIS users on the basis of their stereotypical affinities because clustering algorithms could put together users very affine each other but not linked by friendship relationships and, therefore, not belonging to the same region.

In order $SSMC$ to perform its task, it is necessary to define a parameter capable of "quantifying" the stereotypical similarities of two users u_i and u_l for a context cnt_z. For this purpose let $stereotypes = \{st_1, st_2, \ldots, st_q\}$ be the set of stereotypes into consideration in the SIS; it is possible to consider a q-dimensional space characterized by a dimension for each stereotype.

A SIS user u_i is represented by a point of this space; the w^{th} coordinate of this point is associated with the stereotype st_w and its value coincide with $user\_st\_map_{u_i,cnt_z,st_w}$. As a consequence, each coordinate represents the "stereotypical degree" of u_i as far as the context cnt_z and the stereotype st_w are concerned. Interestingly enough, the distance between two points quantifies the stereotypical dissimilarity of the corresponding users; the higher this distance, the more dissimilar the corresponding users. Moreover, it is necessary to take the following considerations into account: *(i)* each stereotypical degree belongs to the real interval $[0, 1]$; *(ii)* the maximum possible distance d^{max} in our q-dimensional space is the one between the point having all the coordinates set to 0 and the one having all the coordinates set to 1; *(iii)* we are interested in stereotypical affinities of users, instead of their stereotypical dissimilarities.

On the basis of these reasonings a suitable formulation of this parameter is as follows: $st\_sim_{u_i,u_l,cnt_z} = 1 - \frac{d_{u_i,u_l,cnt_z}}{d^{max}}$. Here, d_{u_i,u_l,cnt_z} indicates the distance between the points corresponding to u_i and u_l in our q-dimensional space. Interestingly enough, $st\_sim_{u_i,u_l,cnt_z}$ belongs to the real interval $[0, 1]$.

We are now able to describe the behavior of $SSMC$. Specifically, it consists of two phases: *Phase 1* is devoted to identify the regions of $sis\_st\_map_{cnt_z}$; *Phase 2* is devoted to characterize each region, i.e. to identify the stereotypes predominant in it.

Phase 1 consists of the following steps:

– A friendship graph $friend\_graph_{cnt_z} = \langle fg\_nodes_{cnt_z}, fg\_edges_{cnt_z}\rangle$ is constructed. A node $n_i \in fg\_nodes_{cnt_z}$ is associated with each user u_i of the SIS; an edge $\langle n_i, n_l,\ st\_sim_{u_i,u_l,cnt_z}\rangle \in fg\_edges$ indicates that u_i and u_l

have declared their friendship in at least one social network of the SIS; the weight $st\_sim_{u_i,u_l,cnt_z}$ represents the stereotypical affinity of u_i and u_l for the context cnt_z.
- A graph partitioning algorithm is applied on $friend\_graph_{cnt_z}$; each partition of this graph represents a region of $sis\_st\_map_{cnt_z}$. Our approach is orthogonal to the adopted graph partitioning algorithm; the only requirement is that this algorithm must be capable of operating on very large weighted graphs. Some possible algorithms that could be adopted are those described in [14,4,13].

Phase 2 receives the set $\{sis\_reg^1_{cnt_z}, \ldots, sis\_reg^y_{cnt_z}, \ldots, sis\_reg^m_{cnt_z}\}$ of the regions returned by *Phase 1* and characterizes each region with the suitable stereotypes in such a way as to produce $sis\_st\_map_{cnt_z}$.

In order to perform this characterization, we have considered that several possible scenarios could exist. For instance, given a region $sis\_reg^y_{cnt_z}$, there could be a very predominant stereotype which strongly characterizes it, a set of stereotypes which are predominant over the other ones or, finally, no predominant stereotype.

Our characterization approach aims at facing all these scenarios. For this purpose, given a region $sis\_reg^y_{cnt_z}$ to characterize, it operates as follows:

- For each stereotype, it computes the corresponding average values of the stereotypical degrees of the users of the region. Let $avg\_std_{cnt_z,st_w}$ be the average stereotypical degree, obtained by averaging the stereotypical degrees of all the users of the region, as far as the context cnt_z and the stereotype st_w are concerned.
- It sorts the average stereotypical degrees in the descending order. Let $avg\_std\_list_{cnt_z} = \{avg\_std_{cnt_z,st_1}, \ldots, avg\_std_{cnt_z,st_q}\}$ be the corresponding ordered list.
- It scans $avg\_std\_list_{cnt_z}$, starting from its first element, until it finds an element $avg\_std_{cnt_z,st_r}$ such that $avg\_std_{cnt_z,st_r} > 2 \cdot avg\_std_{cnt_z,st_{r+1}}$, or, alternatively, it reaches the end of the list. In the former case it selects $\{st_1, st_2, \ldots, st_r\}$ as the set of the stereotypes characterizing $sis\_reg^y_{cnt_z}$; in the latter one it concludes that the set *stereotypes* in the whole characterizes $sis\_reg^y_{cnt_z}$.

5 Conclusions

In this paper we have presented $SISO$, a conceptual framework capable of constructing stereotypical maps in a SIS. In the future, we plan to extend the concept of stereotype in such a way as to make it applicable to the resources of a SIS. Then, we plan to provide $SISO$ with components for the construction of resource stereotypical maps. Moreover, we plan to construct a more complex framework having $SISO$ as its central core and which a large variety of plugins could be added to. These plugins could implement the stereotype applications we have presented in this paper, as well as other ones that could be defined in the future. In this way it could be possible to realize a catalogue of plugins allowing the exploitation of stereotypes in various application fields. This way of proceedings is typical of many high-values software framework (think, for instance, of Eclipse and Thunderbird). Finally, we would like to equip $SISO$ with an intelligent system which detects information about the behavior of users in all the possible networks by means of a mobile agent, and analyzes this information by means of Data Mining techniques in such a way as to discover the new "stereotypical trends" and/or the stereotypes that have become obsolete. In this way, it could be possible to maintain the list of stereotypes handled by $SISO$ always updated.

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